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Non-parametric synthesis of laminar volumetric texture

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Abstract

The goal of this paper is to evaluate several extensions of Wei and Levoy's algorithm [1] for the synthesis of laminar volumetric textures constrained only by a single 2D sample. Hence, we shall also review in a unified form the improved algorithm proposed by Kopf *et al.* [2] and the particular histogram matching approach of Chen and Wang [3]. Developing a genuine quantitative study we are able to compare the performances of these algorithms that we have applied to the synthesis of volumetric structures of dense carbons. The 2D samples are lattice fringe images obtained by high resolution transmission electronic microscopy (HRTEM).

1 Introduction

Many tools in image processing, vision and computer graphics invoke image analysis and synthesis, and especially textured images. For this reason, the disciplinary field of texture synthesis is particularly dynamic and very productive with notable applications in image compression, inpainting, image extrapolation or texture mapping. 3D textures are mainly used for texturing volumetric objects trying to increase the realism of the 3D scenario. This research field has lead to the development of many 2D synthesis techniques, but their extension to the 3D environment remains unstable proving itself as a very complex and computational issue. However, the interest of the scientific community for solid texture synthesis gave birth to various families of algorithms.

The procedural family of 3D synthesis algorithms models a solid texture by adjusting some mathematical functions. The range of applicability of the procedural approaches [6, 9, 10] remains sparse, leading mostly to algorithms hard to optimize. In opposition to the global growing character of the solid texture involved by the procedural methods, the local methods [1-4, 11-13] generate the texture one voxel/patch at a time maintaining the coherence of the evolving region with its vicinity. Some of the most underlined synthesis methods based on local optimization from the literature are the exemplar-based synthesis algorithms. These algorithms require only one sample texture as input image and synthesize the solid texture guaranteeing the best possible similitude with the sample.

Allowing a smoother control during the synthesis process, the pixel by pixel synthesis algorithms [1-3, 8, 12] are among the most successful techniques mainly because of their practicability. To assure a reasonable computational complexity, most of the approaches propose efficient searching algorithms combined with a multi-scale implementation capable of capturing patterns at different scales and not increasing the computational load.

We are interested in the synthesis of anisotropic volumetric textures with lamellar structure. The synthesis of such laminar textures from a unique sample is however delicate. It means to infer 3D information from 2D information only. This inference is possible only under some assumptions of anisotropy. A recent 2D/3D extension of the Portilla and Simoncelli [9] parametric algorithm was proposed by Da Costa and Germain [10], relying on the 2D to 3D inference of the 1st and 2nd order statistics and on an original 3D pyramidal decomposition algorithm.

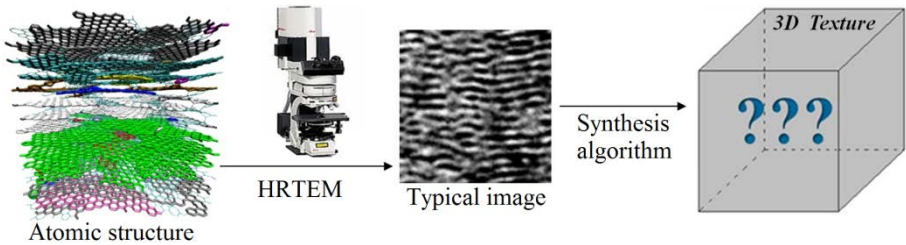


Figure 1: The general schema: obtaining the HRTEM-like snapshots of dense carbons and generating a 3D representation from a single 2D sample.

In the present article, we evaluate various implementations of non-parametric algorithms for the synthesis of laminar textures by means of a both qualitative and quantitative procedure. As an application, we address the particular case of carbon material images obtained by HRTEM [14] showing lamellar structure, objective sketched in Fig. 1. Four examples of such laminar textures are provided in Fig. 2.

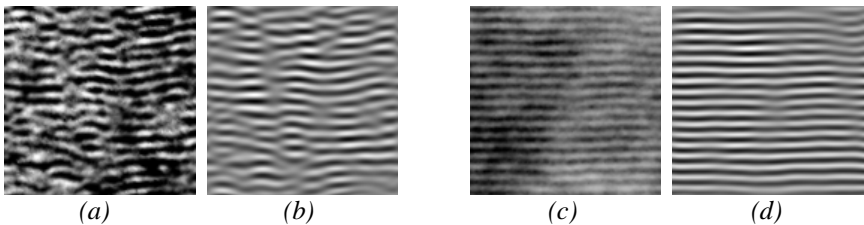


Figure 2: Samples of lattice fringe images of dense pre-graphitic carbons: HRTEM images (a, c) and their filtered versions (b, d). Sample sizes are 128×128 pixels. Resolution is about 5×10^{-11} m per pixel.

2 Non-parametric volumetric synthesis techniques

We are briefly exposing the non-parametric methods we evaluate, namely the algorithms of Wei and Levoy [1, 4] to serve as a basis, Kopf et al. [2] - employed for the improvements brought by its non-parametric global texture optimization procedure and finally Chen and Wang [3] - proposing a high quality texture synthesis by integrating the texture optimization with two new kinds of matching histograms.

2.1 Overview of Wei and Levoy's algorithm

Based on the Markov field hypothesis, this method relies on texture locality (every pixel is predictable from the few pixels in its neighbourhood) and texture stationarity (spatial statistics invariance by translation), assumptions stated in Wei and Levoy[4]. The 2D/3D extension that we put up here is an adaptation of the algorithm of texture synthesis from multiple sources [1]. Starting from a random initialization, we synthesize voxel by voxel by examining the 2D neighbourhood of the current voxel from two orthogonal views of the 3D block (front and side view); this phase implies a TSVQ (Tree-Structured Vector Quantization) search of the best match for each of these 2 neighbourhoods in the same input image. The output pixel corresponds to the average of the two found voxels and we reiterate several times until reaching the same neighbourhoods after 2 consecutive iterations. This 2D/3D extension raises different downsides being constrained by the neighbourhood size and shape or the synthesis scan type. But, by including a multi-resolution scheme it proves to be a well adaptable and largely applicable synthesis method.

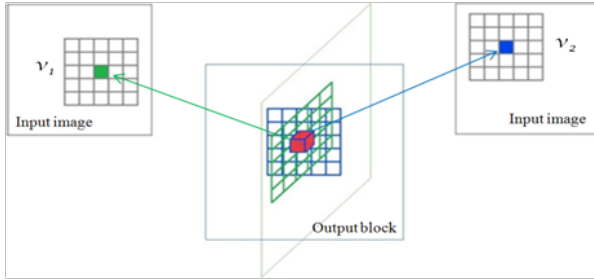


Figure 3: Principle of non-parametric synthesis: extract two neighbourhoods in the output block (front and side view), search the best two neighbourhoods in the input image, combine their central pixel values and modify the output voxel.

2.2 Overview of Kopf's algorithm

Another issue of Wei and Levoy's algorithm resides in the way of combining the information from the front view with the side view as shown in Fig. 2. The simple averaging technique leads to a loss of dynamics between the original and the synthesized texture. One possible answer is to replace the average with a better combination [2, 5] and, in the same time, adding a histogram matching mechanism [2, 6]. Kopf *et al.*[2] propose to give weights to each 2 found voxels and to mix them according to the robust optimization proposed by Kwatra *et al.*[5]. The histogram matching works by adjusting the weight of each voxel engaged in the weighted average that could bring differences between the colour histogram of the 3D result and the colour histogram of the 2D exemplar. In this way the global statistics are preserved and the synthesis doesn't rely only on local decisions. The quality of the results delivered with the technique proposed by Kopf exceeds that of many other methods. Despite this, computing the results by using the weighted average may produce blurry results if the variance of the exemplar voxels is too large [2].

2.3 Overview of Chen and Wang's algorithm

Unfortunately, most of the non-parametric methods are affected by blurring, missing textural patterns or mismatched input/output histograms. To ameliorate these drawbacks,

Chen and Wang [3] propose a new modulus operandi for texture optimization approaches. Mainly, it consists in using two new kinds of histograms – position and index histograms [3] and in updating the output voxel using the discrete solver as Han *et al.*[7]. Prior to synthesis, for every pixel in the exemplar we have to find the k best matches from the exemplar, idea inspired from the natural texture synthesis algorithm proposed by Ashikmin [8]. The set of candidates being constructed, we start a synthesis process similar to Kopf *et al.*[2], but instead of using colour histogram we use the position histogram to adjust the weights. The position histogram records the number of occurrences in the solid texture of the corresponding pixel in the 2D exemplar. The weights are adjusted to get a histogram as uniform as possible. Once the position histogram matching is achieved, the colour histogram matching is achieved also. Index histogram counts the frequency of the voxels candidates in the volume texture. Having all the candidates uniformly distributed means having a well preserved texture. During the search phase, some pixels are restricted according to their index histogram frequency. This algorithm provides results that are similar or in part better than the previous methods.

Whatever the method, a problematic issue remains the choice of the neighbourhood system. The choice of a causal neighbourhood makes the synthesis of a pixel totally dependent on previous pixels and leads in the case of lamellar textures to a higher regularity of synthesized results. The choice of a non-causal neighbourhood can partly overcome this determinism, but now the choice of the scan type may be challenged. Replacing the lexicographical scan type with a completely random walk allows the synthesis of a pixel by freeing itself from its past and so multiplying the possible configurations. However, the convergence time can become prohibitive in this case. To reconcile the deterministic part and the randomness character we propose an alternative scan type, namely the use of space filling curves[17] extended to 3D, like Morton code (Z-curve) or fractal curves(e.g. Hilbert curve) illustrated in Fig. 4.

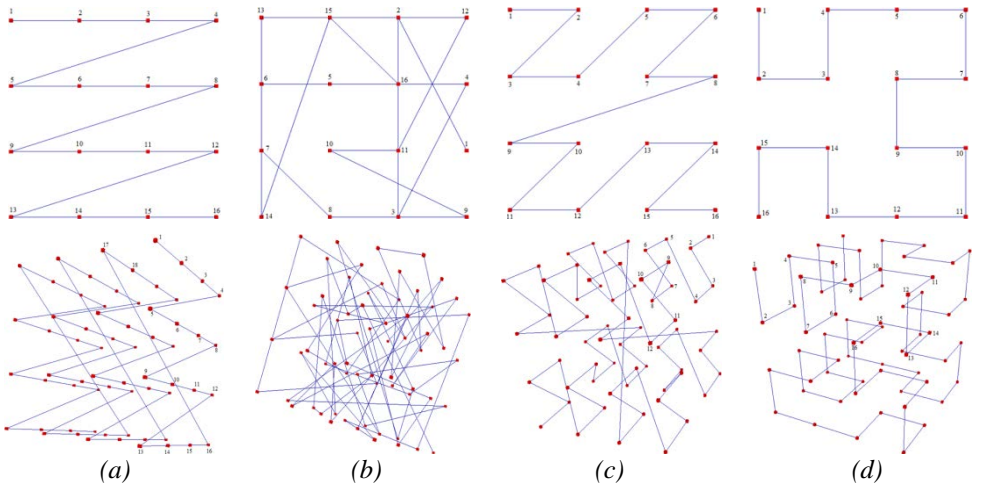


Figure 4: Illustration of different scanning types, in 2-dimensions (the top column) and their corresponding extensions to 3-dimensions (the bottom column): from left to right, *a* - lexicographic path, *b* - random walk, *c* - Z-curve and *d* - Hilbert curve.

3 Experimentation background

We were able to implement different variants of the synthesis algorithm and apply them to the volumetric texture synthesis starting from a single 2D exemplar obtained by microscopy.

Fig. 5a and 5d show the volumetric textures for Wei and Levoy's approach while Fig. 5b and 5e show the results obtained using the backbone of Wei and Levoy but optimized by using the weighted average and the colour histogram matching technique proposed by Kopf *et al.*[2]. In Fig. 5c and 5f are represented the 3D blocks obtained by using the discrete solver plus the index and the position histogram matching technique proposed by Chen and Wang [3]. The experimentation framework consists in using 5 pyramidal levels, non-causal neighbourhoods of size 7x7 pixels and, for Chen and Wang, a set of 15 candidates for each pixel.

3.1 Results

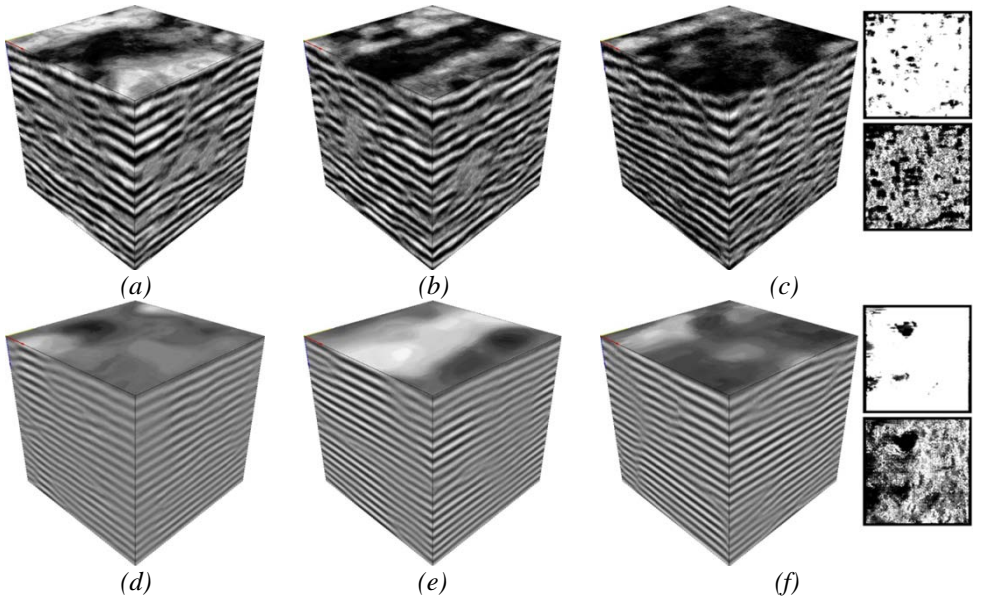


Figure 5: Volumetric results: from top to bottom, the 1st line represents the 3D views of the solid textures obtained after 10 iterations from the raw HRTEM sample in Fig. 2a using, from left to right, Wei and Levoy (a), Kopf (b), Chen and Wang(c); the 2nd line (d, e, f) shows the blocks after applying the same algorithms on the filtered sample in Fig. 2d. For c and f, next to the synthetic block are represented, from top to bottom, the images corresponding to the index and position histograms.

The visual quality of the results is relatively convincing, in terms of dynamics and structure. Measuring the results based on our human perception, we can say that the 3D results and the original images seem to have been created by the same underlying process (see the images from Fig. 2 and Fig. 5 for analogy). The perceptual comparison of the result in Fig. 5d with the ones in Fig. 5e or 5f reveals that, in some cases, the Wei and

Levoy's algorithm is not capable to preserve the gray-levels, which is not the case for the algorithms involving histogram adjustments. In addition, taking into account the size of the structures in determining the number of synthesis levels and the neighbourhood size is a critical point in terms of synthesis quality.

3.2 Quantitative evaluation

The results interpretation using only our senses remains subjective, so we are constrained to compare them objectively. This original quantitative study evaluates the results taking into account the results gray level dynamics (first order statistics), but also their spatial statistics (autocorrelations) and morphological properties like fringe length, tortuosity and orientation. It aims to evaluate the algorithms capacity to reproduce a 3D texture respecting the statistical properties of the exemplar.

The quantitative indicators from Fig. 6, Fig. 8 and Fig. 9 reveal the 3D textures tendency towards the same structure observed on the HRTEM images.

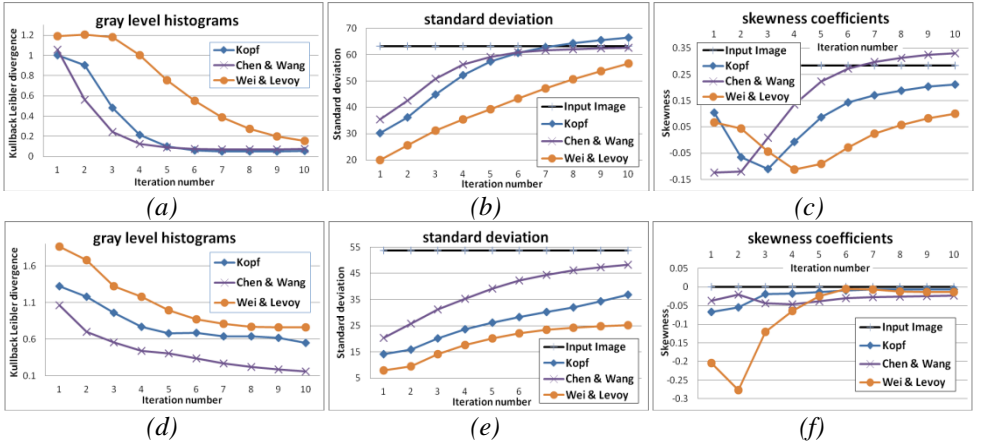


Figure 6: Plots of different indicators, corresponding to the objective comparison of the 3D textures obtained by synthesizing the HRTEM texture in Fig. 2a (the 1st line) and the sample in Fig. 2d (the 2nd line): gray level histograms (a, d) and 1st order statistics (b, e - standard deviation; c, f - skewness). The procedure consist in comparing input image statistics with the ones obtained after a multi-2D solid blocks analysis (b, c, e, f) or by computing Kullback-Leibler divergence between the histograms of the exemplar and the output block (a, d).

The comparison of the results dynamics from Fig. 6 confirms the visual conclusion attributed to Wei and Levoy's algorithm not being able to conserve contrast because of the averaging operation when combining the two orthogonal views. This objective comparison of the evolution of the 3D blocks statistics towards the ones from the 2D sample strengthens the visual assumptions relative to the significant improvements brought by the histogram matching techniques.

As for the structural properties of the synthesized blocks, we have compared in Fig. 8 the local orientations of the multi-2D block relative to the input sample based on a structure tensor estimated on a 7×7 neighbourhood inspired from Bigun et al.[15] using image orientation field and its associated orientation histogram as exemplified in Fig. 7.

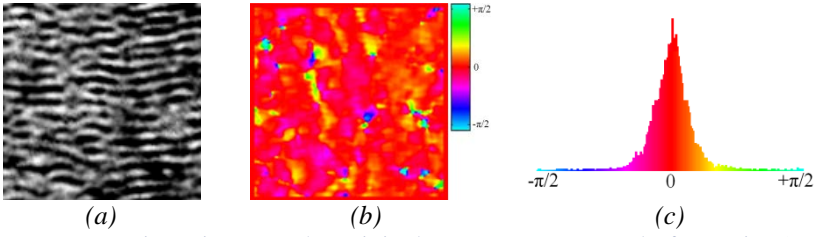


Figure 7: Texture orientation: *a* – the original raw HRTEM sample from Fig. 1a; *b* - the correspondent orientation field and the colour bar giving the correspondence between colours and orientations; *c* – the orientation histogram computed from the orientation field.

The left plot from Fig. 8 confirms the impression that in some cases the proposed algorithms tend to produce textures more regular than that of the input image, and iterating more doesn't resolve the reproduction of patterns. This phenomenon may be related to the deterministic character of the algorithms, based on local decisions, which tends to produce these very regular or repetitive textures. But this can be also caused by the limited size of the input image which is not large enough to guarantee a sufficient diversity at the output, or the limited size of the output block of which periodicity somehow imposes a certain regularity.

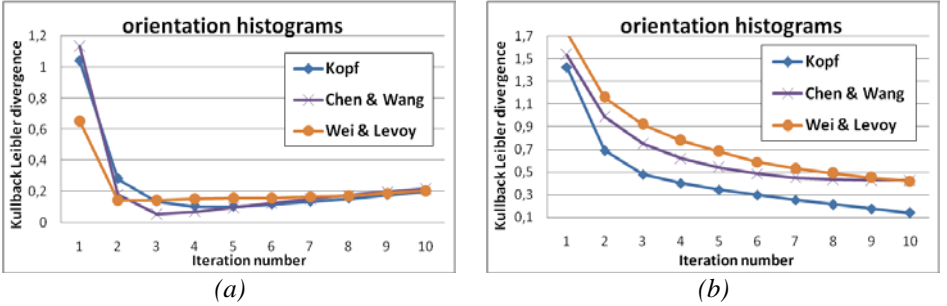


Figure 8: Plots of the spatial structure variation indicator: the Kullback - Leibler divergence between the orientation histograms of the exemplar and the output blocks obtained by applying the algorithms on the exemplar in Fig. 1a (the left plot - *a*) and on the sample in Fig. 1d (the right plot - *b*).

The general convergence tendency is also certified by the comparison of the morphological properties. It consists in tracking the texture level curves and describing the elongated patterns contained within the texture. We address the orientation and pattern length measurement techniques as described by Da Costa *et al.*[16] to extract textural features (fringes) and compute their lengths and tortuosity. We count the frequency of appearance of the fringe lengths and classify them in function of their lengths. Fig. 9a shows the frequency of the fringe lengths in the input image in comparison to the frequency of the fringe lengths in the multi-2D synthesized 3D block where fringes were retrieved by manipulating the front slices and the side slices in the block. Similar, we built tortuosity classes and compare the tortuosity values distribution in Fig. 9b.

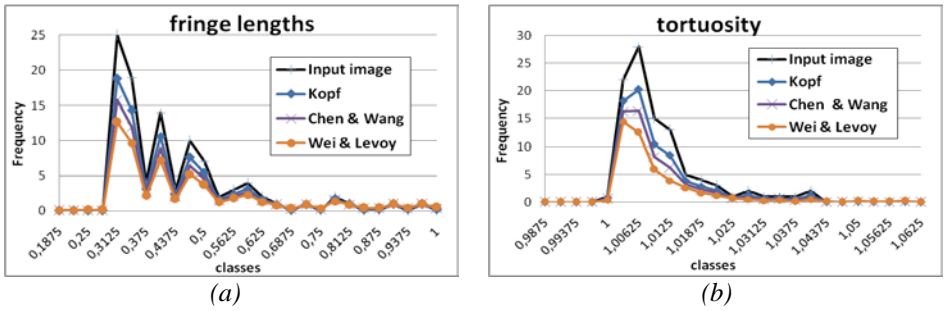


Figure 9: Plots of the morphological structure indicators: *a* - the distribution of fringe lengths in the input raw HRTEM image from Fig. 2a and in the volumetric synthesized textures from Fig. 5a-5c; *b* - the distribution of the tortuosity values corresponding to the same input image and output blocks used in *a*.

4 Conclusions

In this paper, we have brought about several algorithms that achieve with success solid texture synthesis starting from a 2D texture exemplar. Results interpretation was accompanied by an original experimental procedure marking a qualitative and objective evaluation. As an application, we have used these algorithms to the synthesis of anisotropic HRTEM images of dense carbons. Apart from certain limitations, the obtained results are convincing in term of preserving texture gray-levels and texture structure properties.

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